Foundation Model- Ecommerce Recommendation

Using Hetergeneous Network and Hybrid Recommendation

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***Abstract*—E-commerce recommendation system can be seen as a network among items and users, a complex connections among these. So, the recommendation works better when we find the actual intention behind a purchase of items for a particular user. In this paper, we tried to capture this intention of the purchase, that is, to capture different path's summary of a particular user, and its purchased items, and item's respective metadata.**

***Index Terms*—Heterogenous Network, Metapath, Sentence Embeddings, BERT**

I. Introduction

METADATAS play a very important role in describing an item, which indirectly helps an user whether he/she likes to purchase the item or not. For example, user u1 buys a product i1 because product i1 is sold by his favourite store s1. But an user u2 buys the same product i1 because i1 has category c1 and u2 has already purchased from c1 category before, so he would like to purchase from the same category c1 again. So, we see, the story behind a same purchase might be different and it will help in future recommendations. That's why we should need to capture this story that is the path summary between different metadata-item-user paths and measure it.

A foundation model for recommendation systems serves as a fundamental framework upon which more specific recommendation models can be built. It typically involves the development of a base model that encompasses essential components and algorithms necessary for generating recommendations. These components may include data preprocessing, feature engineering, algorithm selection, and evaluation metrics. The foundation model aims to provide a solid starting point for recommendation system development by offering a comprehensive understanding of the data and algorithms involved. It often incorporates best practices and established techniques from the field of recommendation systems, allowing developers to build upon existing knowledge and methodologies.

In this paper, we will be using two levels of recommendation models, and feed the output of first recommendation model into the second one.

II. Recommendation Model 1

We are using an user-prompt. The user-prompt will be provided by the user which will describe what he/she is looking for. Now this string (user-prompt) will be acting as an input to our first recommendation model. Our first recommendation model uses BERT. The 'title' of each item is fed into BERT and are converted to proper sentence embeddings. These embeddings are stored which can be used later. Then we are taking our input string and calculating its similarity with our title embeddings. The similarity measure we used here is cosine similarity. Then we are showing top 20 most similar title along with its product-id.

These are our first recommendations. These can be treated as the recommendations exactly what the user is looking for.

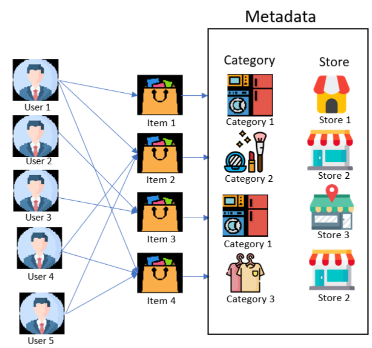

Fig. 1: Heterogeneous Network in E-commerce platform

III. Motivation for next recommendation model

Now that we got first level of recommendation system, next idea that should come to our mind is how to find more deeper and good future recommendation based on what the user wants. This is where our heterogeneous network comes into play.

IV. Heterogeneous network Recommendation System

As discussed earlier, the e-commerce platform can be thought of a complex heterogeneous network of users and items and its meta-datas. Fig 1 gave an illustration of how the network might look like. Item 1 and item 3 have the same category but different store, whereas item 2 and item 4 have different category but same store. Also, we can observe that users who bought item 4 also buys item 2. These pieces of information are very essential for our future recommendation. For starting we have assumed that the user wants to buy the product searched by him/her. Thus, the first recommendations in section III will be assumed to be bought by the user. This will establish the connecting paths of our user and items.

V. Metapath

Meta-paths, situated within the framework of information network schemas, delineate potential connections between two types of entities via various paths.

A meta-path $P = A_0 R_1 \to A_1 R_2 \to \ldots R_k \to A_k$ is a path in a network schema $GT = (A, R)$, which defines a new composite relation $R_1 R_2 \ldots R_k$ between type A_0 and A_k, where $A_i \in A$ and $R_i \in R$ for $i = 0, \ldots, k$, $A_0 = \mathrm{dom}(R_1) = \mathrm{dom}(P)$, $A_k = \mathrm{range}(R_k) = \mathrm{range}(P)$, and $A_i = \mathrm{range}(R_i) = \mathrm{dom}(R_{i+1})$ for $i = 1, \ldots, k-1$. Here, $\mathrm{dom}()$ defines the domain of a certain relationship, and $\mathrm{range}()$ defines the range.

We use p to denote the paths in information networks and P to denote meta-paths. Based on the above definition, one can notice that meta-paths are the types for paths in information networks. Previous studies suggest that meta-paths can be used to facilitate entity similarity or proximity measurement and similarity semantic disambiguation.

VI. User Diffusion Matrix

Given a meta-path $P = R_1 R_2 \ldots R_k$ with domain $\mathrm{dom}(P) =$ user and range $\mathrm{range}(P) =$ item, let $P' = R_2 \ldots R_k$ with domain $\mathrm{dom}(P') =$ item and range $\mathrm{range}(P') = \mathrm{range}(P) =$ item. We define the user preference diffusion score between user i and item j along P by extending the PathSim measurement as follows:

$$s(u_i, e_j|P) = \sum_{e \in I} \frac{2 \times R_{u_i,e} \times |\{p_{e \to e_j} : p_{e \to e_j} \in P'\}|}{|\{p_{e \to e} : p_{e \to e} \in P'\}| + |\{p_{e_j \to e_j} : p_{e_j \to e_j} \in P'\}|}$$

where $p_{e \to e_j}$ is a path between e and e_j, $p_{e \to e}$ is a path between e and e, and $p_{e_j \to e_j}$ is a path between e_j and e_j.

The user preference diffusion score between user u_i and item e_j contains two parts: (1) the observed user-item interactions associated with u_i, and (2) the connectivity between the items that u_i is interested in and potential items of interest, represented by e_j. Notice the connectivity between items is defined as the number of paths between these items following the meta-path P and normalized by the visibility of the items so the diffusion score does not overly favor popular items.

VII. Appropriate User and Item Representation

In this simplified example, Fig. 2, we examine a small information network featuring two users (u1 and u2), three items (i1, i2, and i3), and five metadata entities (a1 through a5). These entities are interconnected as illustrated in Figure 2. In this figure, solid red links denote observed user implicit feedback, while purple dotted links signify diffused user preferences.

When calculating the diffusion score, we utilize the meta-path user–item–metadata–item (denoted as P). For instance, with implicit feedback data R, if we know that $u1$ purchased item $i2$, we can infer that there exists one path between $i1$ and $i2$ following the specified meta-path. Additionally, there are two paths each between $i1$ and $i1$, and between $i2$ and $i2$.

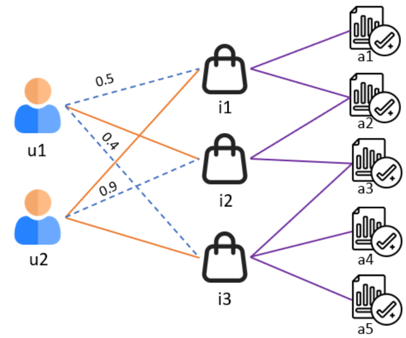

Fig. 2: Example network

Applying the implicit feedback data, we find that the user preference diffusion score from $u1$ to $i1$ under meta-path P is 0.5. Similarly, other diffusion scores in this example can be calculated accordingly.

By measuring the diffusion scores between all users and all items along the meta-path P, we can generate a diffused user preference matrix $\tilde{R} \in \mathbb{R}^{m \times n}$. Here, $\tilde{R}_i$ represents the potential preferences of user u_i if they explore the network for new content following meta-path P.

By repeating this process with L different meta-paths, we can calculate L different diffused user preference matrices accordingly. These user preference matrices are denoted as $\tilde{R}^{(1)}$, $\tilde{R}^{(2)}$, ..., $\tilde{R}^{(L)}$.

VIII. Appropriate User and Item Representation and Ranking of Items

We denote $\tilde{R}^{(q)}$ as the diffused user preference matrix along the q-th meta-path. Drawing from the intuition and principles of matrix factorization-based recommendation methods, we derive low-rank user and item matrices from each diffused preference matrix. These low-rank matrices serve as the latent representations of users and items, reflecting the semantic meaning of the corresponding meta-path.

Using the low-rank matrix factorization technique, we decompose the diffused matrix $\tilde{R}^{(q)}$ as follows:

$$(U\hat{\ }(q), V\hat{\ }(q)) = \mathrm{argmin}_{U,V} \|\tilde{R}^{(q)} - UV^\top\|_F^2$$

$$\text{subject to } U \geq 0, V \geq 0,$$

where $U\hat{\ }(q) \in \mathbb{R}^{m \times d}$ represents users and $V\hat{\ }(q) \in \mathbb{R}^{n \times d}$ represents items, with $d < \min(n, m)$. $U\hat{\ }(q)_i$ denotes the latent feature for user u_i along the q-th meta-path, and $V\hat{\ }(q)_j$ denotes the latent feature for item e_j along the q-th meta-path, respectively.

We define a global recommendation model as follows:

$$r(u_i, e_j) = \sum_{q=1}^{L} \theta_q \cdot U\hat{\ }(q)_i (V\hat{\ }(q)_j)^\top$$

where θ_q is the weight for the q-th user and item low-rank representation pair. Considering the non-negative property of the features, we incorporate $\theta_q \geq 0$ as an optimization constraint.

Now that we have $r(u_i, e_j)$, we can iterate through all e_j) in our dataset and rank them in increasing order, hence getting perfect recommendations.

Algorithm 1 Recommendation Models

Require: User prompt
Ensure: Recommendations based on user's prompt
1: **Output1**: Recommendations based on the user's immediate needs
2: **Output2**: Future relevant recommendations based on the user's interests
3: **Model 1:**
4: Generate sentence embeddings for all product titles using BERT.
5: Calculate the similarity between the user prompt and each embedding.
6: Select the top n products with the highest similarity.
7: These products constitute **Output 1.**
8: **Model 2:**
9: Create a new user profile and use Output 1 as the list of products purchased by this new user.
10: Compute the meta-path values $s(u_{\text{new}}, e_j|P)$ for all items j belonging to the user's profile and append them to the R_k matrix for all k.
11: Apply Non-negative Matrix Factorization (NMF) to R_k for all k. Obtain $U\hat{}(k)$, $V\hat{}(k)$, and $\theta^{(k)}$ for each k.
12: Calculate $r(u_{\text{new}}, e_j)$ using provided equation.
13: Rank the products in descending order and display them.
14: These products constitute **Output 2**.

IX. Data

We will be utilizing two datasets, namely "meta_Appliances" and "Appliances," obtained from Amazon. This is a large-scale Amazon Reviews dataset collected in 2023. You can download the datasets from the following links:

The "Appliances" dataset has dimensions (2128605, 10), indicating 2,128,605 rows and 10 columns. Among these, there are 1,755,732 unique user IDs. The "meta_Appliances" dataset has dimensions (94327, 16), containing information on 94,327 items.

Furthermore, we investigate any missing or incomplete data entries and assess their impact on the overall dataset quality. Handling missing data appropriately is crucial to ensure the reliability and accuracy of our analysis results.

To create our working dataset, denoted as "df," we merged these datasets and performed data cleaning. As a result, "df" has dimensions (2128605, 7), with the following columns: 'parent_asin', 'user_id', 'main_category', 'title', 'features', 'store', and 'categories.' Due to computational constraints, we will work with a subset of 1000 rows from "df."

	parent_asin	user_id	main_category	title	features	store	categories
0	B01N0TQ0OH	AGKHLEW2SOWHNMFQIJGBECAF7INQ	Tools & Home Improvement	Geesta 12-Pack Premium Activated Charcoal Wate...	[EXCEPTIONAL QUALITY AND VALUE: Brew clean, de...	Geesta	[Small Appliance Parts & Accessories, Coffee &...
1	B07DD37QPZ	AHWWLSPCJMALVHDDVSUGICL6RUCA	Tools & Home Improvement	Essential Values 18 Pack Compatible Replacemen...	[BEST VALUE - Our 18 Pack Of Fine Polyester Re...	Essential Values	[Appliances, Parts & Accessories, Dryer Parts ...
2	B082W3Z9YK	AHZIJGKEWRTAEOZ673G5B3SNXEGQ	Tools & Home Improvement	279838 Dryer Heating Element by Romalon with R...	[★【BUY WITH CONFIDENCE】 For any reason you're ...	Romalon	[Appliances, Parts & Accessories, Dryer Parts ...
3	B078W2BJY8	AFGUPTDFAWOHHL4LZDV27ERDNOYQ	Amazon Home	Filterlogic UKF8001 Water Filter, Replacement ...	[The replacement for Maytag UKF8001 refrigerat...	FilterLogic	[Appliances, Parts & Accessories, Refrigerator...
4	B08C9LPCQV	AELFJFAXQERUSMTXJQ6SYFFRDWMA	Tools & Home Improvement	Sikawai 279816 Dryer Thermal Cut-off Kit Repla...	[]	Sikawai	[Appliances, Parts & Accessories, Dryer Parts ...

Fig. 3: df dataset

X. Insight into the Dataset

Next, we explore the relationships between different metadata features such as 'store' and 'categories'. By analyzing these relationships, we aim to uncover patterns and associations that could inform our recommendation algorithms and enhance their performance.

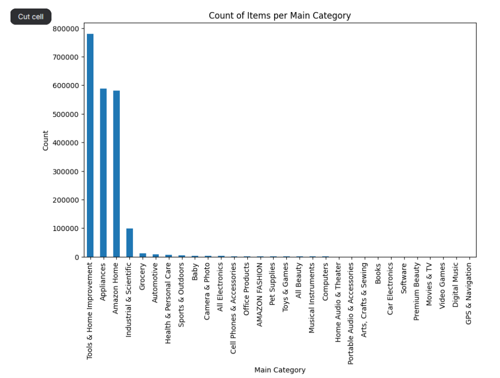

Fig. 4: main-category frequency

We delve into the dataset to gain valuable insights. We begin by examining the distribution of categories in the 'main_category' column. From the bar graph representation, it's evident that certain categories such as 'Tools & Home Improvement', 'Amazon Home', 'Industrial & Scientific', and 'Appliances' exhibit a high frequency compared to others. This suggests potential biases or trends within the dataset that may influence our analysis and modeling approaches.

We explore insights into the 'store' column of our dataset. The 'store' column represents the different stores from which the products were sourced.

We begin by examining the unique values in the 'store' column. There are a total of 13,165 unique stores represented in the dataset. This indicates a diverse range of sources for the products.

We delve into insights related to the 'categories' column of our dataset. The 'categories' column contains lists of categories to which each product belongs.

We begin by exploring the variety and distribution of categories across the dataset. Each product can belong to multiple categories, as represented by the lists in this column. [Fig. 3.]

Through these insights, we aim to gain a deeper understanding of the dataset characteristics and structure, which will guide our subsequent analysis and modeling efforts.

XI. Creating User Diffused Matrices

In this section, we create three diffused matrices, denoted as R1, R2, and R3, using Equation (4) with different meta-paths.

A. R1: Category Metapath

- We compute the user preference diffusion score between users and items based on the meta-path involving categories. - Using Equation (4), we calculate the user-item preference scores for this meta-path.

	B0759KR8JX	B01AQHRBDU	B07N57SMSK	B000KI3O1O	B00DZU89JG	B0BMFFJJ7R	B01AZXTBPG	B01BIDPHYQ	B0773GCJ4F	B09YQ1CT3G	...	B07FN7BLLV	B07RG6R5J5	B094783WQ3	B06XR96P3Z	B07F926
0	1.000000	0.666667	0.500000	1.000000	0.500000	0.285714	1.000000	1.000000	0.500000	1.000000	...	0.500000	0.500000	0.666667	0.750000	
1	0.666667	1.000000	0.666667	0.666667	0.666667	0.400000	0.666667	0.666667	0.666667	0.666667	...	0.666667	0.666667	1.000000	0.666667	
2	0.500000	0.666667	1.000000	0.500000	0.750000	0.285714	0.500000	0.500000	1.000000	0.500000	...	0.500000	1.000000	0.666667	0.500000	
3	1.000000	0.666667	0.500000	1.000000	0.500000	0.285714	1.000000	1.000000	0.500000	1.000000	...	0.500000	0.500000	0.666667	0.750000	
4	0.500000	0.666667	0.750000	0.500000	1.000000	0.285714	0.500000	0.500000	0.750000	0.500000	...	0.500000	0.750000	0.666667	0.500000	

Fig. 5: User Diffused Matrix for Cateogry Metapath

B. R2: Storing Metapath

- Similarly, we compute the user preference diffusion score between users and items based on the meta-path involving stores. - We apply Equation (4) to obtain the user-item preference scores for this meta-path.

	B0759KR8JX	B01AQHRBDU	B07N57SMSK	B000KI3O1O	B00DZU89JG	B0BMFFJJ7R	B01AZXTBPG	B01BIDPHYQ	B0773GCJ4F	B09YQ1CT3G	...	B07FN7BLLV	B07RG6R5J5	B094783WQ3	B06XR96P3Z	B07F926
0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	
1	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	
2	0.0	0.0	1.0	1.0	1.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	
3	0.0	0.0	1.0	1.0	1.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	
4	0.0	0.0	1.0	1.0	1.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	

Fig. 6: User Diffusion Matrix for Store Metapath

C. R3: Main Category Metapath

- Finally, we compute the user preference diffusion score between users and items based on the meta-path involving main categories. - The provided equation is applied to compute the user-item preference scores for this meta-path.

	B0759KR8JX	B01AQHRBDU	B07N57SMSK	B000KI3O1O	B00DZU89JG	B0BMFFJJ7R	B01AZXTBPG	B01BIDPHYQ	B0773GCJ4F	B09YQ1CT3G	...	B07FN7BLLV	B07RG6R5J5	B094783WQ3	B06XR96P3Z	B07F926
0	1.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	
1	0.0	1.0	1.0	1.0	1.0	0.0	1.0	0.0	1.0	0.0	...	1.0	0.0	0.0	0.0	
2	0.0	1.0	1.0	1.0	1.0	0.0	1.0	0.0	1.0	0.0	...	1.0	0.0	0.0	0.0	
3	0.0	1.0	1.0	1.0	1.0	0.0	1.0	0.0	1.0	0.0	...	1.0	0.0	0.0	0.0	
4	0.0	1.0	1.0	1.0	1.0	0.0	1.0	0.0	1.0	0.0	...	1.0	0.0	0.0	0.0	

Fig. 7: User Diffused Matrix for Main-Category Metapath

Through these calculations, we derive three diffused matrices representing user preferences based on different meta-paths. These matrices will serve as valuable inputs for our recommendation models.

XII. Testing-Taking a real time input

```
# User prompt
user_prompt = "Water Pump"
```

Fig. 8: User Prompt

We start with the user prompt ”Washer Pump”. After applying our initial model, we obtained the following outputs[Fig. 9.], which notably align with our user prompt. Moving forward, we'll construct a dataset comprising user IDs for the new user and product ASINs for the products obtained from the output.

```
Whirlpool W10276397 Water Pump B00DZU7RTO
Whirlpool 3363892 Water Pump for Washer B0053F7PIC
Whirlpool 12544002 Water Valve B00ECX0DIU
Whirlpool W10217563 Clamp for Washer B005B45GHC
Whirlpool W10219643 Water Valve B0156NELL4
Whirlpool W10130913 Water Pump for Washer B005AR76M8
Whirlpool W10130913 Water Pump for Washer B001DHLC1K
FloodSafe Washing Machine Hose B001AZL5O4
Whirlpool W10409079 Drain Pump-Water B00LHR2ACQ
Whirlpool 213045 Tub-to-Pump Hose B00DZUB48O
Whirlpool 8066184 Motor Pulley for Washer B0053F8O5U
W10217563 Whirlpool Washer Clamp B004Q3VKR4
Whirlpool 8182415 Water Pump for Washer B0053F9710
```

Fig. 9: Some Products from Output 1

For each item and each of the three meta-paths, we'll compute its user diffused values. Subsequently, we'll perform non-negative matrix factorization (NMF) for each matrix to extract the latent user features, latent meta-path features, and their respective weights.

Next, we'll calculate the rating (denoted as ”r”) for the new user using the formula provided. We'll then sort the results in descending order and display the top 20 products. It's worth noting that the products obtained in our second model are highly relevant. Not only do they suggest the user's required product (”Washer Pump”), but they also include various parts and replacements associated with ”Washer Pump”. This indicates the effectiveness and relevance of our algorithm in providing tailored recommendations.

	product_id	title
0	B08FHR16M6	W10780048 Washing Machine Suspension Rod Kit (...
1	B08GHH1SL9	Lifetime W10130913 Washer Drain Pump by Seente...
2	B00DM8J11Q	Supco OTHF LP338, 1, White
3	B07PJ7ZBZZ	WPW10730972 Washer Drain Pump Replaces 8540024...
4	B082SJ5PKX	4681EA2001T Washer Drain Pump Motor by Beaquic...
5	B01N7EVUZE	Replacement Whirlpool Dishwasher Pump W1034826...
6	B00AH60G3S	LG Electronics 4681EA1007G Washing Machine Dra...
7	B08NPXYZTL	Washer Rotor Hub Assembly MBF618448 for LG Was...
8	B005AR76M8	Whirlpool W10130913 Water Pump for Washer
9	B00DH21WN2	Whirlpool OEM Factory Kenmore Washer Water Dra...
10	B08FHTYVBS	2023 Upgraded DC97-05280W Washer Suspension Ro...
11	B07PJ485FQ	Ansoon 202203 Washer Drain Pump Replacement Pa...
12	B07NDNJDLK	Washer Pump 137108000, 134051100
13	B07YFDB6Y6	4681EA2001T Washer Drain Pump Motor Compatible...
14	B09T86N1XY	4Pcs Washer Suspension Rod Kit Replaces For Am...
15	B07KQDPYYD	OEM Pump W10536347
16	B00AYBL3H4	LG Electronics 6501KW2002A Washing Machine Rot...
17	B07P1G6MYW	Reliable 4681EA2001T (AP5328388) Washer Drain ...
18	B00DM8KZBQ	Whirlpool W10536347 Drain Pump
19	B08QHSG1RM	W10780045 Washer Suspension Rod kit 4pcs(26.7i...

Fig. 10: Some Outputs from Output 2

XIII. Metrics Evaluation

To assess the performance of our recommendation system, we compare the predicted recommendations with the actual products purchased by users. This comparison is conducted based on the similarity between the titles of the recommended products and the purchased ones.

A. Methodology

We utilize sentence embeddings generated by BERT to represent the titles of the recommended products and the purchased ones bought by the user. Subsequently, we compute the cosine similarity between these embeddings as a measure of similarity.

	user_id	similarity
0	AHJGIPM2BSL2PQIP2223Y2WVVAPQ	0.947719
1	AE6A7ZAYSWGMQST3PJR7FZADOTQQ	0.800713
2	AGJ54MNRCWZ6J3WLBIAKAWIYACBA	1.000000
3	AEOV4JIKICCCT52K5NT3V32A6Y3Q	0.808326
4	AHYK42AQSVMIBUVC3YPFS7WOZ5FA	0.913700
5	AHKNU4DNSSZYUFUOBEUBGLF7I7EA	0.876119
6	AGUSNX5HTVMEJRILEXU77D6TUJRQ	0.783085
7	AHTLWVDXSMG5YMVMEIWWOU6XBZMA	0.918325
8	AEOS2PM3Y2DVJDENZEPE3ZS4L3XQ	0.798206
9	AFVAUF5XDUB2H6MA2ND3VFEO5E2Q	0.938971
10	AHIJ6IYL5BGEIBCPHIX6AGZLIIPA	0.858082
11	AGPJYEDRSKZAUINOVRFX37NOBMDA	0.926775
12	AGC5BQ6YP23V6F355TPLA5GEM3AQ	0.836348
13	AGTPFF7YIMF55CZR2YXYJE3PEZKA	0.815617
14	AEHAWSOCS6TU65YOJ34MFXTPJATA	0.864747
15	AESSQ65L2NFXTNEZY26U3GCRDVJA	0.907638

Fig. 11: Similarity between actual products bought by some users and predicted recommendations

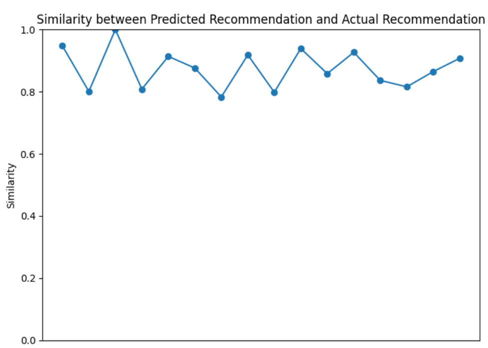

Fig. 12: Graph showing the similarity measure of our model

B. Results

The evaluation results demonstrate the effectiveness of our recommendation system in providing relevant suggestions to users. The computed similarity scores indicate the degree of similarity between the recommended products and the purchased ones, thereby providing insights into the performance of our system. The average similarity given by our model is 0.8746482357382774.

C. Conclusion

An average similarity score of 0.8746482357382774 achieved by our model reflects its robust capability in accurately capturing semantic similarities between recommended products and those actually purchased by users. This high level of similarity underscores the effectiveness of our recommendation system in understanding user preferences and delivering relevant suggestions.

Through our metrics evaluation, we validate the ability of our recommendation system to accurately suggest products that align with users' preferences. By comparing predicted recommendations with actual purchases, we gain valuable insights into the performance and effectiveness of our system.

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